

Barriers to reproducibility: misalignment of career incentives and open science best practices

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We are on the precipice of a sea change in how research is conducted. Funder mandates and changing expectations around scientific reproducibility have resulted in a new set of open science best practices (OSBP) for research. These practices include, but are not limited to, data and code sharing, hypothesis preregistration, registered reports, and open peer review. With these changes come challenges and potentially unanticipated side-effects. In particular, here I will highlight what I see as the biggest mismatches between the career incentives of the field of neuroscience and OSBP, from the perspective of an early career researcher.

Data and code sharing is encouraged or required by some journals and funders, but this practice has not yet seen widespread adoption - “data available upon reasonable request” remains the default. For example, a recent editorial by an editor who requested data from the authors of 41 papers stated that 97% did not provide raw data (1). The main limitations to data and code sharing are time, training, and opportunity cost - which can be offset by institutional investment. Keeping code bases up to date and data tidy requires training and time on the part of students, staff, and researchers. The work this takes may limit the rate of progress on other activities such as data collection or manuscript or grant writing. On the other hand, most projects occur in a team science environment where good data hygiene benefits all. When institutions provide the infrastructure to facilitate basic automation abilities needed to, for example, process simple data without requiring home-brewed code, it then becomes easier to share that code in a repository. Then, errors can be discovered

through reanalysis, other groups can reuse the data, the public as well as other scientists trust results more when code is available, and data faking is disincentivized.

Preregistration refers to the process of outlining hypotheses and analysis plans prior to data collection, to prevent bad practices such as “hypothesizing after results are known” or “p-hacking” (performing repeated tests without controlling for false positive rate). Registered reports (RRs) are a manuscript format that involves peer review of the introduction and methods sections of the paper prior to data collection. These sections are approved in stage 1 review, which grants in-principle acceptance of the stage 2 manuscript that includes results and discussion. The main advantage to early-career researchers of RRs is the drastically shorter time from review to acceptance - since methodological issues are dealt with prior to data collection, corrections can be made in response to review to an extent that is not possible in traditional review. One potentially inconvenient reality is that the results of RRs are more likely to be negative than positive, and without the option to quietly relegate results to the file drawer, researchers must accept that their favorite theory may not prove correct.

Open review refers to peer review where signed or anonymized reviewer comments are shared alongside the published manuscript. The benefits of this approach are that the review quality and rigor can be independently evaluated. This may encourage reviewers to be more constructive and civil, as adversarial reviewers risk their unprofessional behavior becoming public knowledge rather than being shrouded behind internal journal reviewer ratings. Potential downsides include the public

nature of what is usually a “closed door” critique - a bad review going viral could bring unwanted attention to the reviewer and authors, and editors will need to weigh such outcomes during the peer review process. The pressure to write an open review may mean it takes longer for reviewers to gather their thoughts. For early career researchers, the risk of signing a negative review from a higher-status researchers’ work may be a barrier to participation, and therefore ECRs should not be pressured to sign reviews.

Despite potential downsides, reproducibility needs to be a priority for neuroscience to maintain integrity of the science itself, and to ensure continued buy-in from stakeholders such as funding agencies, politicians, and the lay public whose tax dollars fund most research. Recently, multiple scientific fields have faced intense backlash and criticism, which could likely have been averted if OSBP were followed. For example, high-profile social psychology findings on “power posing” were found to not be replicable (2); the “amyloid hypothesis” of Alzheimer’s disease has been called into question after decades dominating the field (3); and both economics and genetics have both suffered pernicious issues with errors generated by the use of Excel for data analysis (4,5). In the clinical sciences, a starkly low compliance rate with the mandate to post research study outcomes on clinicaltrials.gov highlights the barriers to widespread adoption of OSBP (6,7). This is not to mention more nefarious issues such as falsifying data, which would be automatically disincentivized if data and code sharing were universally required.

Currently, OSBP are not the norm, leading the early adopters to sit on what may be the initial “bleeding edge” of the coming wave, where they assume a higher degree of risk but also have the opportunity to be thought leaders in their fields. Centers such as the Stanford Center for Reproducible Neuroscience, the Center for Open Science, and the Open Science Foundation are all bellwethers of this change. Early career researchers from undergraduates to postdocs are in the most ideal position to join the second wave “cutting edge” by incorporating

OSBP into their work, because their career stage involves an expectation of training in new techniques. Being on the cutting edge offers some of the prestige of the bleeding edge but with less risk. Developing a code base can serve as part of application portfolios for graduate programs or postdocs - computationally savvy labs may value coding skills as much as “traditional” academic skills like manuscript writing or public speaking. Sharing data demonstrates commitment to transparency, replicability, and robustness of science. Preregistration and submission of registered reports eliminates the expectation for trainees to waste time p-hacking results from data that doesn’t support initial hypotheses, and can contribute to a record of scientific productivity that emphasizes rigor.

Perhaps the biggest challenge is not the implementation of OSBP - the open source tools are there, and the training on how to use them is largely available online for free. Instead, researchers fear that individual career costs incurred will outweigh benefits to science. Institutions can play an important role in offsetting this fear, both by monetarily supporting the software, automation processes, and other infrastructure necessary for OSBP, but also by creating a culture of excellence that rewards OSBP (e.g. in tenure review). Public response to several recent high-profile retractions suggest that attitudes and norms are changing in the broader scientific community. Nobel prize winner Dr. Frances Arnold retracted a paper after data irregularities were found and posted a “*mea culpa*” on Twitter (8). In addition to modeling how to graciously admit an error, the 5K+ likes on the tweet and 300+ comments were largely supportive and even congratulatory, suggesting the field finds such transparency refreshing. Other researchers have taken a similar approach, also with a largely positive reception (9), suggesting that slowly but surely incentives are changing to better align with OSBP. Perhaps when it comes to open science best practices, the biggest thing to fear is fear itself.

References

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